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Structural Equation Modeling Semiparametric in Modeling the Accuracy of Payment Time for Customers of Credit Bank in Indonesia

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ABSTRACT

Credit risk assessment is crucial for financial institutions to ensure loan repayment. To enhance the prediction accuracy of creditworthiness and timely repayment, this research employs semiparametric structural equation modeling (SEM) to analyze the factors influencing credit repayment timeliness. The research was conducted to apply semiparametric SEM modeling to the timeliness of paying credit. Semiparametric SEM is structural modeling in which two combined approaches of parametric and nonparametric approaches are used. The analysis method in this research is semiparametric SEM with a nonparametric approach using a truncated spline. Truncated splines are chosen for their flexibility, ability to model complex relationships, continuity, interpretability, and strong performance in nonparametric regression tasks. The data in the study were obtained through questionnaires distributed to Bank X mortgage debtors and are confidential. The quetionnairs in the Likert scale, with five options. The study used 3 variables consisting of one exogenous variable, one intervening endogenous variable, and one endogenous variable. The results showed that: (1) the effect of capacity and willingness to pay variables on timeliness of payment is significant; (2) modeling the capacity variable on willingness to pay also produces a significant estimate; (3) the effect of the capacity variable on the timeliness of payment variable is not influenced by the willingness to pay variable as an intervening variable; and (4) the R^2 value of 0.763 or 76.33% indicates that the model has good predictive relevance. To continue to develop punctuality of paying credit, banks need to pay attention to the financial stability of consumers. Besides the financial stability, banks should pay attention to the sense of responsibility that customers have.

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A. INTRODUCTION

In 1934, Structural Equation Modeling (SEM) was developed by Wright a development of path analysis as a means of studying the direct influence and indirect influence of several variables, where some variables are seen as causes, and other variables are seen as effects (Bollen et al, 2022). SEM is a combination of two models, namely the structural model and the measurement model. The model that describes the relationships that exist between latent variables is called a structural model. Meanwhile, the model that describes the relationship between latent variables and observed variables (indicators) is called the measurement model.

Structural Equation Modeling (SEM) is a statistical analysis method used to solve complex problems or phenomena using a structural approach. SEM allows the analysis of direct and indirect relationships between variables, as well as allowing the analysis of causality and indirect effects (Hair & Alamer, 2022). SEM involves the estimation of a series of regression equations that are used to describe the relationships between variables. This method is widely used in various fields, including business, psychology, and sociology, to analyze the relationships between variables and to test hypotheses (Darwin & Khairul, 2020).

According to Civelek (2018), the linearity assumption is an important assumption in SEM. In SEM there is a relationship that needs to be known between latent variables. The purpose of linearity analysis is to determine the shape of the relationship between variables, so that the shape of the model is influenced by the assumption of linearity. The model formed from the relationship between variables in SEM has a different approach depending on the results of testing the linearity assumption. One way to test the linearity assumption is to use Ramsey's RESET Test (Ubaidillah et al., 2022).

The approach taken for structural modeling in SEM is similar to modeling using path analysis. If the linearity assumption is fulfilled, meaning that the relationship formed is linear, the approach will use parametric path analysis. If the linearity assumption is not met, meaning that the relationship formed is not linear and the form of the regression function assumed in the relationship between variables is unknown, the approach taken uses nonparametric path analysis (Ubaidillah et al., 2022). However, if the results of the linearity assumption have several linear relationships the shape of the regression function between variable relationships is known and there are several non-linear relationships and the shape of the regression function between variable relationships is unknown, it can use semiparametric path analysis which is a combination of parametric and nonparametric approaches (Rasyidah, Fernandes, Iriany, et al., 2021).

One of the nonparametric path analysis approaches is spline. According to Ubaidilla et al. (2022), spline is used in nonparametric path analysis because it can follow the pattern of relationships between exogenous variables and endogenous variables. Spline is divided into two types, namely truncated spline and smoothing spline. The nonparametric approach used in this study is truncated spline. In addition to spline, another nonparametric path analysis approach can be approached with Kernel which is very dependent on weights (Rasyidah et al. 2021). Sometimes there is data that has a relationship between exogenous variables and mediating endogenous variables and pure endogenous variables that have a partially parametric and nonparametric relationship. This can be because when the process of modeling data in the form of exogenous and endogenous variable relationships cannot always use only one approach. Thus, it can be clarified that SEM is a combination of structural models and measurement models (Khairi et al., 2021). Developments that can be made based on SEM analysis, namely on semiparametric structural models.

According to Du and Bentler (2022), estimating the structural equation model function can be used OLS (Ordinary Least square) if the approach used is parametric. However, there is one condition where OLS is no longer efficient in estimating the structural model function. So the WLS (Weighted Least Square) method was developed (Xu et al., 2023). Weighted Least Square (WLS) is a parameter estimation method that can accommodate the correlation between equations in path analysis. Estimation of path coefficients is done by WLS optimization which accommodates the correlation between equations using weighted in the form of the inverse of the error variance-covariance matrix. According to Kang et al. (2020), It is possible that the model produced by the OLS method still contains outliers that will affect the diversity of the rest of the models, while the WLS method minimizes the outliers in the data. The WLS method has better flexibility than the OLS method.

Homeownership credit (KPR) is a type of credit provided by banks to help individuals or families buy or build houses as a place to live (Nasution, 2021). Mortgages are usually given with certain conditions, such as collateral for the property to be purchased, as well as a predetermined interest rate and payment period. Mortgages can be divided into two types: Subsidized mortgages and non-subsidized mortgages. Subsidized mortgages are loans provided with the help of the government to help people who have low income to buy a house. Non-subsidized mortgages are loans provided without government assistance and usually have higher interest rates (Ginting, 2020).

Previous research conducted by Syafriana et al. (2023), examines the development of nonparametric structural equation modeling on simulated data. In this study, Syafriana used 4 variables consisting of one exogenous variable, two intervening endogenous variables, and one endogenous variable. From this study, it was found that with simulated data, all relationships were significant and could be explained by 91% of exogenous variables on endogenous variables, while the remaining 9% was explained by other variables outside the research variables in the model.

Previous research was also conducted by Maisaroh et al. (2024), which examines the Comparison of mediation effects on interaction and multigroup approaches in structural equation modeling PLS in the case of bank mortgages. In this study, the approach used is a parametric approach using PLS. In addition, all measurement models formed are formative measurement models. The structural model in this study is formed based on two exogenous variables, two endogenous variables, and one moderating variable. The result of that research is the testing of indirect effects on moderation with interaction and multigroup approaches are not much different. The bootstrap interval bias in the multigroup approach is smaller than the bootstrap interval bias in the interaction approach. The Q-square Predictive Relevance value in both methods is quite high, indicating that the model is good. On the Current Collectibility Status group Q^2 is 89.3%, in the incurrect Collectibility Status Q^2 is 84.2%. While in the interaction approach, Q^2 is 70.4%. Researcher recommend a multigroup approach to data that has categorical moderation variables because differences between groups can be directly observed without adding interaction variables in the model.

There are 5 principles in determining credit decisions, these 5 principles are generally called the 5Cs. 5C includes Character, Capacity, Capital, Guarantee, and Condition (Izzalqurny et al., 2022). In this research we will use one of the five 'C' variables, namely Capacity. Capacity is an assessment by the banking sector regarding the business carried out by the prospective debtor as a means of making a profit so that it can repay the loan. The research give the result that to extend credit, several steps must be completed: field assessment, approval by the credit department head, and final disbursement. Creditworthiness is evaluated using the 5C framework: character, capacity, capital, collateral, and conditions. While the 5C process itself hasn't changed since the pandemic, lenders have intensified credit analysis to reduce the risk of loan defaults.

In this study, SEM development will be carried out in the form of a semiparametric approach with a case study, namely KPR / HOC (*Kredit Pemilikan Rumah*/Home Ownership Credit). The semiparametric approach is carried out with a nonparametric approach, namely spline, and a parametric approach, namely linear. In this study, the spline used is a truncated spline which is highly dependent on knot points. The study was conducted with three variables, namely one exogenous variable, one intervening variable, and one endogenous variable. The measurement model used is a reflective measurement model. So, this research aims to know the development of SEM semiparametric in the Timeliness of Credit Payment in Banking and the influence between latent variables.

B. METHODS

The data used in this study is banking data which is confidential by banks. In this study, a questionnaire was used as a research instrument. Respondents of this study were customers who took mortgages / HOCs at Bank X in Indonesia. . The scale used is a Likert Scale consisting of 5 items. The sampling technique method used is judgment sampling by taking 100 respondents as samples. Respondents can choose 1 of 5 items based on the questions and statements that are most suitable according to the respondent. For validty test used covergent and discriminant validty, and for reliability test used Corbach's Alpha. The variables used in this study consist of three variables, namely one exogenous variable (X_1), one intervening endogenous variable (Y_1), and one endogenous variable (Y_2). With the number of indicators being three, five, and three for variables X_1, Y_1, and Y_2 respectively. The indicators used are reflective. The variables and indicators used in this study are listed in Table 1.

Table 1. Variable and Indicator

Variable	Indicator
Capacity ($\boldsymbol{X_1}$)	Customer income ($X_{1.1}$)
	Ability to pay installments($X_{1.2}$)
	Ability to complete credit on time ($X_{1.3}$)
Willingness to pay ($\boldsymbol{Y_1}$)	Consultation ($Y_{1.1}$)
	Documents prepared($Y_{1.2}$)
	How and where to pay credit ($Y_{1.3}$)
	Payment deadline($Y_{1.4}$)
	Fund allocation($Y_{1.5}$)
Timeliness of payment ($\boldsymbol{Y_2}$)	The desire to always pay on time ($Y_{2.1}$)
	Always on time to pay per month ($Y_{2.2}$)
	Frequency on time ($Y_{2.3}$)

The analysis technique used in the research is SEM. According to Lee (2007), SEM is one of the multivariate analysis techniques that aims to analyze the relationship between variables that are more complex when this analysis is compared to other analyses such as multiple regression and factor analysis. To facilitate understanding of SEM modeling, the relationship between variables can be visualized in the form of a conceptual model. The conceptual model in this study is presented in Figure 1.

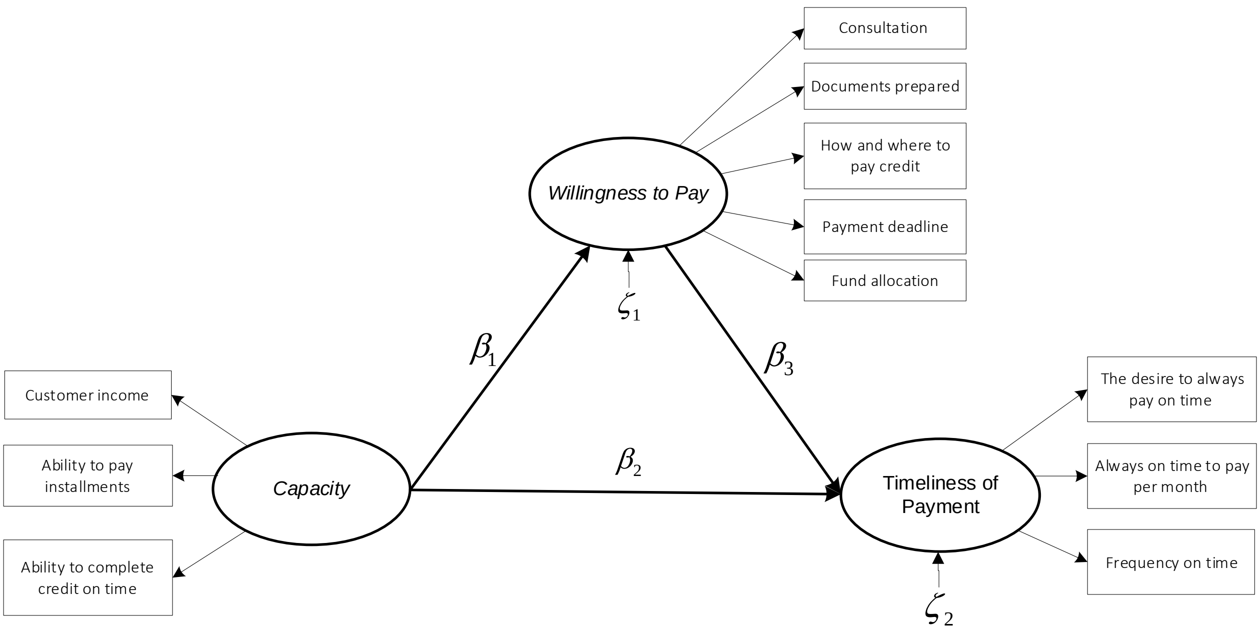

Figure 1. Conceptual Model

The details about the steps that need to be taken in semiparametric SEM modeling are as follows bellow:

1. Input Data

The data used is confidential banking customer data. Respondents who were given questionnaires were customers of the bank who made mortgages.

2. Determine variables and variable indicators.

Variable indicators are set on exogenous variables, intervening variables, and endogenous variables by the concept model formed. The concept model that has been formed can be seen in Figure 1.

3. Designing structural models and measurement models

The structural model is designed by determining the relationship between latent variables. The measurement model is designed by determining the nature of the indicators of the existing variables. Then form a research path diagram construction which can be seen in Figure 2.

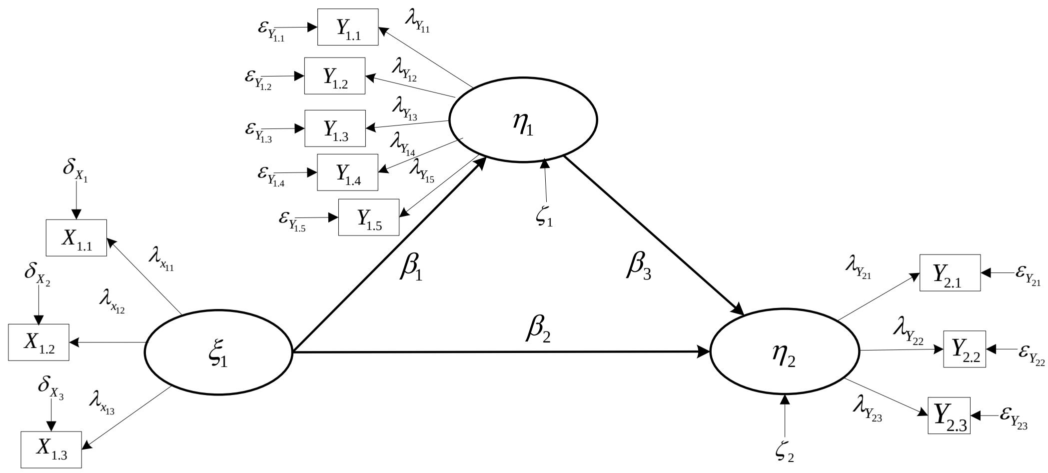

Figure 2. Path Diagram

4. Convert the path diagram into equations such as equation (1) and equation (2).

$$\eta_1 = \beta_1\xi_1 + \zeta_1 \tag{1}$$

$$\eta_2 = \beta_2\xi_1 + \beta_3\eta_1 + \hat{\delta}(\eta_{1i} - K)_+ + \zeta_2$$
$$(\eta_{1i} - K)_+ = \begin{cases} \eta_{1i} - K, & \eta_{1i} > K \\ 0, & \eta_{1i} < K \end{cases} \tag{2}$$

K is the knot point that will be calculated for the optimal knot point first.

5. Conducting factor analysis on indicators

Factor analysis is carried out on indicators of research variables that have reflective measurement types. The reflective measurement model can be written in Equation (3) and Equation (4).

$$X_{ij} = \lambda_{x_{i.j}}\xi_i + \delta_{X_{ij}} \tag{3}$$
$$Y_{gk} = \lambda_{y_{g.k}}\eta_g + \varepsilon_{Y_{gk}} \tag{4}$$

The factor analysis used in the study is written in matrix form as in equation (5).

$$\boldsymbol{X} = \boldsymbol{cF} + \boldsymbol{\varepsilon} \tag{5}$$

Where **X** is a matrix of normally distributed variables with a center value vector $\tilde{\mu}$ and var-cov matrix **Σ**. **c** is a matrix of loading factors, and **F** is a factor. However, factor analysis is often the initial analysis performed when encountering problems to obtain new variables or latent variables. Thus, the new variable must have data in the form of factor scores. If S is inputted as the input data matrix for the new variable, the factor score can be calculated as in equation (6).

$$\boldsymbol{S-Fa = c'S^{-1}(x_j - \bar{x})} \tag{6}$$

6. Testing the linearity assumption

To determine the shape of relationships between variables and also the relationship between latent variables should be tested by linearity assumptions test using Ramsey's RESET Test. If the results of the linearity assumption test provide results that the existing relationship between variables is linear, the next approach is a parametric approach to estimating the path coefficient in the SEM structural model. But, when the results of the linearity assumption test give the result that the existing relationship between variables is not linear and the visible relationship pattern is unknown, the relationship between these variables is estimated with a nonparametric approach. More detail about the step how to do and also how to get the conclusion for the linierity assumption in Ramsey's RESET Test can be explained as follows. Ramsey's RESET Test for linearity testing is based on the hypothesis: $H_0$is $\beta_{j+1} = \beta_{j+2} = 0$, $y_i = f(x_i)$ is a linear function; j= 1,2,..,k vs; $H_1$is There is a minimum one of $\beta_{j+k} \neq 0$, $y_i = f(x_i)$ is not a linear function. In testing linearity, there is a procedure that needs to be done using Ramsey's RESET Test as follows:

a. Forming the regression Y_i toward $X_1, X_2, X_3, \dots, X_p$, then find the quadratic and qubic equation regression. So that the estimated value can be seen in Equation (7), Equation (8), and Equation (9).

$$\hat{Y}_i = \hat{\beta}_0 + \sum_{j=1}^{k} \hat{\beta}_j X_{ji} \tag{7}$$

$$\hat{Y}_i^2 = \hat{\beta}_0 + \sum_{j=1}^{k} \hat{\beta}_j X_{ji}^2 \tag{8}$$

$$\hat{Y}_i^3 = \hat{\beta}_0 + \sum_{j=1}^{k} \hat{\beta}_j X_{ji}^3 \tag{9}$$

b. Forming new regression equation Y_i^* towards $X_1, X_2, X_3, \dots, X_p$ and adding exogenous variable $Y_i{}^2$ dan $\hat{Y}_i^3$. Then, estimate $\hat{Y}_i^*$ obtained using Equation (10).

$$\hat{Y}_i^* = \hat{\beta}_0^* + \sum_{j=1}^{k} \hat{\beta}_j^* X_{ji} + \hat{\beta}_{k+1}\hat{Y}_i^2 + \hat{\beta}_{k+2}\hat{Y}_i^3 \tag{10}$$

c. Calculating coefficient of determination (R^2) from regression old can be written as R_o^2

$$R_o^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{11}$$

d. Calculating coefficient of determination (R^2) from regression new can be written as R_n^2.

$$R_n^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i^* - \hat{Y}_i^*)^2}{\sum_{i=1}^{n}(Y_i^* - \bar{Y}^*)^2} \tag{12}$$

e. The next step is to test the linearity between the predictor variables on the response variable with the formula as in Equation (13).

$$F_{stat} = \frac{(R_{new}^2 - R_{old}^2)/m}{(1 - R_{new}^2)/(n-k)} \sim F_{(\alpha,m,n-k)} \tag{13}$$

Based on hypothesis testing above, F-statistics is distributed by F distribution. If $F_{stat} > F_{(\alpha;m,n-k)}$ or $p - value < \alpha$, so it can be concluded that H_0 is rejected therefore the model is not linear and vice versa.

7. Perform semiparametric SEM.

In this step, the most optimal knot point will be sought before performing nonparametric estimation using a truncated spline. Truncated spline is the method used to model nonparametric model in non-linear relationship for the flexibelity. To see the most optimal knot point can be seen from the smallest GCV results (Eubank, 1999; Fernandes et al., 2014; Utami et al., 2020). The GCV equation is written in Equation (14).

$$GCV(\boldsymbol{K}) = \frac{MSE(\boldsymbol{K})}{[n^{-1}trace(\boldsymbol{I} - A(\boldsymbol{K}))]^2} \tag{14}$$

There $MSE(\boldsymbol{K}) = n^{-1}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$, $\boldsymbol{K}$ is Matriks knot point (points $\boldsymbol{K} = (K_1, K_2, .., K_k)^T$) and $\boldsymbol{A}(\boldsymbol{K})$ is obtained from

$$A(\boldsymbol{K}) = \boldsymbol{X}[\boldsymbol{K}](\boldsymbol{X}[\boldsymbol{K}]^{\boldsymbol{T}}\boldsymbol{X}[\boldsymbol{K}])^{-\boldsymbol{1}}\boldsymbol{X}[\boldsymbol{K}]^{\boldsymbol{T}} \tag{15}$$

where is obtained from Equation (16).

$$\boldsymbol{X}[\boldsymbol{K}] = \boldsymbol{X}[K_1, K_2, \dots, K_k] = \begin{bmatrix} 1 & \mathrm{X}_1 & \cdots & \mathrm{X}_1^p & (\mathrm{X}_1 - \mathrm{K}_1)_+^p & \cdots & (\mathrm{X}_1 - \mathrm{K}_k)_+^p \\ 1 & \mathrm{X}_2 & \cdots & \mathrm{X}_2^p & (\mathrm{X}_2 - \mathrm{K}_1)_+^p & \cdots & (\mathrm{X}_2 - \mathrm{K}_k)_+^p \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 1 & \mathrm{X}_n & \cdots & \mathrm{X}_n^p & (\mathrm{X}_n - \mathrm{K}_1)_+^p & \cdots & (\mathrm{X}_n - \mathrm{K}_k)_+^p \end{bmatrix} \tag{16}$$

8. Perform simultaneous hypothesis testing to determine the significance of parameters and functions and function estimation.

Perform function estimation using WLS. Weighted Least Square (WLS) is a parameter estimation method that is able to accommodate the correlation between equations in path analysis. Estimating the path coefficient is done by WLS optimization which accommodates the correlation between equations using weight in the form of the inverse of the error variance-covariance matrix . At the same time estimating the measurement model.

9. Interpretation based on the path coefficient and goodness of fit of the model formed.

C. RESULT AND DISCUSSION

1. Ramsey's RESET Test

Ramsey's RESET Test used to test the linearity assumption. If there is relationships that are non-linear and have unknown data pattern types, so that relationships between variables use a nonparametric approach. Then, if there is relationships that are linear, so that relationships between variables use a parametric approach, as shown in Table 2.

Table 2. Linearity Test Results (Ramsey's RESET)

Relationship between Variables	p-value	Result
$X_1 \to Y_1$	0.922	Not significant
$X_1 \to Y_2$	0.199	Not significant
$Y_1 \to Y_2$	<0.001	Significant

Based on the test results in Table 2, it can be seen that there are two linear relationships and a nonlinear relationship. When the result shows not significant it means that the relationship between latent variables is linear. But, when the result shows significant, then it can be called that the relationship between latent variable is non-linear or we can assumed that the model can be a nonparametric model. The two linear relationship between Capacity (X_1) and Willingness to Pay (Y_1) also relationship between Capacity (X_1) and (Y_2). There is a nonlinear relationship between the variables of Willingness to Pay (Y_1) and the (Y_2), while the rest have a linear relationship. Because there is two approach in this model, then the analysis that will be carried out at the next stage is semiparametric SEM.

2. The Optimal Knot

Generalized Cross Validation (GCV) used to know the optimal knot point layout. The smallest GCV is known by the optimal knot point. The knot point and GCV value shows in Table 3.

Table 3. Optimal Knots

No	Knot	GCV	R^2_{adj}
1	0.350	0.731	0.764
2	-1.542	0.734	0.759

Based on the results of determining the optimal knot point, it can be seen that the smallest GCV is owned by a linear model with a 1-knot point, which is 0.732. Based on the results of GCV calculations in Table 3, it can be seen that knot point 0.350 has the smallest GCV values so it is determined as the optimal knot point. So that in the modeling that is formed later there is 2 regimes because the knot point divide the plot of relationships. So, there will be different relationships patterns between variables. That is when the values of Y < 0.350 and Y > 0.350.

3. Measurement Model

The results of the measurement model of the indicators of each variable can be seen based on outer loading. Outer loading has been presented in Table 4.

Table 4. Loading Factor

Variable	Indicator	Outer loading	p-value
X_1	X_{11}	0.780	0.002
	X_{12}	0.616	0.003
	X_{13}	0.880	0.003
Y_1	Y_{11}	0.701	0.003
	Y_{12}	0.869	0.005
	Y_{13}	0.702	0.004
	Y_{14}	0.625	0.003
	Y_{15}	0.610	0.003
Y_2	Y_{21}	0.775	0.003
	Y_{22}	0.801	0.004
	Y_{23}	0.761	0.003

Based on Table 4, it is found that the strongest indicator in the capacity variable (X_1) is the ability to complete credit on time (X_{13}) with an outer loading value of 0.880. The strongest indicator on the willingness to pay variable (Y_1) is the document prepared (Y_{12} with an outer loading value of 0.869. The strongest indicator on the timeliness of payment variable (Y_2) is always on time to pay per month (Y_{22}) with an outer loading value of 0.801. The strongest indicators indicate that these indicators are the indicators that best reflect each variable.

4. Structural Model Function

Based on testing the semiparametric SEM structural model that has tested the linearity assumption, it is found that there are two linear relationships and one nonlinear relationship. The knot we found the result of GCV before that in this model just has a single knot, that is why in this model especially in the semiparametric model the knot that written in the function is just one knot or just a single knot. In SEM, the interpretation of eash coefficient in function it depend the sign of coefficient. It can be negative or positive. The function formed from structural modeling can be seen in equation (17).

$$\begin{gathered}\hat{f}_1 = \hat{\beta}_1 X_{1i} \\ \hat{f}_2 = \hat{\beta}_2 X_{1i} + \hat{\beta}_3 Y_1 + \hat{\delta}(Y_{1i} - K)_+ \\ (Y_{1i} - K)_+ = \begin{cases} Y_{1i} - K, & \eta_{1i} > K \\ 0, & \eta_{1i} < K \end{cases}\end{gathered} \tag{17}$$

Based on this equation, the next analysis is carried out, namely testing the direct and indirect effects between variables. Table 5 provides the results of testing the direct effect of the model that has been obtained.

Table 5. The Results of Testing the Direct Effect

Relationship	Coefficient	Estimation	P-Value	Result
X_1 towards Y_1	$\hat{\beta}_1 X_{1i}$	0.356	0.002	Significant
X_1 towards Y_2	$\hat{\beta}_2 X_{1i}$	-0.101	0.069	Significant $\alpha = 0.1$
Y_1 towards Y_2	$\hat{\beta}_3 Y_{1i}$	0.497	0.003	Significant
	$\hat{\delta}(Y_{1i} - K)_+$	-1.219	0.004	Significant

The indirect effect in the model occurs in the relationship between X_1 and Y_2 through Y_1. The results of indirect effect testing are in Table 6.

Table 6. The Results of Testing the Indirect Effect

Relationship	Coefficient	P-value	***Result***
Condition when $Y_1 \leq \boldsymbol{K_1}$			
$\boldsymbol{X_1}$ towards $\boldsymbol{Y_1}$	0.356	0.003	Significant
$\boldsymbol{Y_1}$ towards $\boldsymbol{Y_2}$	0.497	0.004	Significant
$\boldsymbol{X_1}$ towards $\boldsymbol{Y_2}$ through $\boldsymbol{Y_1}$	0.176	0.048	Significant
Condition when $Y_1 > \boldsymbol{K_1}$			
$\boldsymbol{X_1}$ towards $\boldsymbol{Y_1}$	0.356	0.005	Significant
$\boldsymbol{Y_1}$ towards $\boldsymbol{Y_2}$	-1.219	0.004	Significant
$\boldsymbol{X_1}$ towards $\boldsymbol{Y_2}$ through $\boldsymbol{Y_1}$	-0.686	0.014	Significant

Thus, equation (17) can be completed with the path coefficient in the semiparametric SEM model as in equation (18).

$$
\begin{gathered}
\hat{f}_1 = 0.356\, X_{1i} \\
\hat{f}_2 = -0.101\, X_{1i} + 0.497\, Y_1 - 1.219\, (Y_{1i} - 0.350)_+ \\
(Y_{1i} - 0.350)_+ = \begin{cases} Y_{1i} - 0.350, & Y_{1i} > 0.350 \\ 0, & Y_{1i} < 0.350 \end{cases}
\end{gathered}
\tag{18}
$$

Total effect testing is carried out to determine direct and indirect testing. The results of the total effect are presented in Table 7.

Table 7. The Results of Testing the Total Effect

Relationship	Regime	Direct Effect	Indirect Effect	Total Effect
X_1 towards Y_1	-	0.356*	-	0.356*
X_1 towards Y_2	$Y_1 \leq K_1$	-0.101**	0.176*	0.074**
	$Y_1 > K_1$		-0.686*	-0.786*
Y_1 towards Y_2	$Y_1 \leq K_1$	0.497*	-	0.497*
	$Y_1 > K_1$	-1.219*	-	-1.219*

Note:* Sig. with $\alpha = 0{,}05$ and **Sig. with $\alpha = 0{,}1$

It can be seen that the smallest GCV also has the highest adjusted R-Square value, which is 0.763. This indicates that 76.3% of the data variability can be explained by a linear model with one knot point.

5. Relationship Between Variable

Testing the direct effect between capacity (X_1) on willingness to pay (Y_1), obtained a structural coefficient value of 0.434 with a p-value of 0.003 which means significant. Thus, there is a significant direct effect between capacity (X_1) on willingness to pay (Y_1). The structural coefficient is positive, indicating that the relationship between the two is positive. That is, the more capacity (X_1) increases, the more willingness to pay (Y_1) of Bank X mortgage customers will increase. This can occur in the condition of customers who have a stable and high enough income. Customers who have greater financial capacity tend to have a strong commitment to homeownership as a long-term investment.

Testing the direct effect between capacity (X_1) on timeliness of payment (Y_2), obtained a structural coefficient value of -0.104 with a p-value of 0.071 which means significant. So, there is a significant direct influence between capacity (X_1) on the timeliness of paying (Y_2) of Bank X mortgage customers. This can occur in conditions where customers with large financial capacity may have high spending preferences or make other investments that require large cash flows, resulting in delays in mortgage payments.

Testing the direct effect between willingness to pay (Y_1)on the timeliness of paying (Y_2), there are two special conditions, namely the first condition of willingness to pay (Y_1)of Bank X mortgage customers can affect the timeliness of paying (Y_2)by 0.502 with a p-value of 0.004 which means significant. This can happen to customers who have a sense of responsibility in paying on time and mature financial planning. The first condition can be interpreted where customers have a strong commitment to mortgages because customer value mortgages as long-term investments and in these conditions, customers have sufficient and stable finances to pay mortgages. In the second condition, the willingness to pay (Y_1)of Bank X mortgage customers can affect the timeliness of paying (Y_2) by -1.221 with a p-value of 0.003 which means significant. This can occur when customer conditions have sudden financial changes or can occur with customers who have an unstable attitude so that they have not considered long-term planning for mortgage payments.

The results of the indirect effect between capacity (X_1) on the timeliness of paying (Y_2) through willingness to pay (Y_1) there are two conditions, where the first condition explained the effect of the relationship $Y_1 \leq K_1$, the second explained the effect of the relationship $Y_1 > K_1$. The results of the indirect relationship can explain that when the relationship $Y_1 \leq K_1$ obtained a coefficient value of 0.502. After reaching a point at a value of 0.350, the relationship of willingness to pay (Y_1)to the timeliness of paying (Y_2) changes the coefficient value, which is -1.221. While the relationship between capacity (X_1) on willingness to pay (Y_1) has a coefficient value of 0.434. Based on the results of the direct effect, it can be clarified that the results of the indirect effect of capacity (X_1) on timeliness to pay (Y_2) through willingness to pay (Y_1) get a p-value of 0.013 which means significant. So, from these results, it can be explained that capacity (X_1) can affect the timeliness of paying (Y_2) through willingness to pay (Y_1).

D. CONCLUSION AND SUGGESTIONS

Based on the analysis that has been done. It can be concluded that the semiparametric SEM obtained is good for modeling the development of punctuality with a truncated spline approach. All variables have a significant influence on the development of punctuality. Whenerver, the relationship between capacity and timeliness to pay is negative. Also the relationship between willingness to pay and timeliness of payment has two different conditions in its influence according to customer conditions. Therefore for bank need to continue to develop a punctuality of paying credit, banks need to pay attention to the financial stability of consumers. Beside the financial stability, banks should pay attention to the sense of responsibility that customers have. Because financial stability and a sense of customer responsibility are very influential in the exact time customers pay mortgages. For further research can develop semiparametric SEM with another nonparametric approach such as Smoothing spline or Kernel.

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